

FUNCTIONAL NETWORKS AS A BEST-MODEL SELECTOR IN COMPUTATIONAL INTELLIGENCE HYBRID MODELS FOR PETROLEUM RESERVOIR CHARACTERIZATION

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Abstract. Functional Networks (FN) has been known as a computational intelligence (CI) technique with excellent functional approximation capability. When the input data is supplied to the networks, the output is determined by a set of neurons, which are defined by a function. FN is an advancement of the Artificial Neural Network technology. Feature selection is an important part of the model building process where the dimensions of input spaces are reduced for better performance. The feature selection process has been used in petroleum reservoir modeling but the non-linear selection capability of FN has not been studied. In this paper, we used the model selection segment of the learning algorithm of FN to select the dominant input parameters for the prediction of porosity and permeability of petroleum reservoirs using hybrid CI paradigm. The effect of the FN-based feature selection process on the improved performance of a Type-2 Fuzzy Logic-Support Vector Machine (T2F-SVM) hybrid model was investigated. T2FL was used to extract rules directly from the best models selected by the FN algorithm and the output was then passed to SVM for the final prediction process. The results of this were then compared with that of T2F-SVM hybrid without the FN component. The results showed that the FN-T2F-SVM performed better with higher performance indices than the T2F-SVM, hence suggesting the feature-selection capability of the learning algorithm of FN.

Keywords: hybrid, feature selection, Fuzzy Logic, Support Vector Machines, Functional Networks.

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INTRODUCTION

In machine learning, feature selection is the method of selecting a subset of features that are most relevant for building robust learning models. By removing redundant features from a dataset, the feature selection process helps to improve the performance of learning models by alleviating the effect of the curse of dimensionality [1], enhancing generalization capability, speeding up the learning process due to the reduced dimensionality and improving model prediction capability [2, 3]. Feature selection also helps users to acquire better understanding about their data by revealing the parameters that are dominant and the degree of strength of their relationship to the target variable.

From a theoretical perspective, it has been shown that optimal feature selection for supervised learning problems demands an exhaustive search for all possible subsets of features of the chosen cardinality [2, 3]. It is impractical if large numbers of features are available. For practical supervised learning algorithms,

the search is for a satisfactory set of features instead of an optimal set [4]. Feature selection algorithms typically fall into two categories: feature ranking and subset selection. The Feature ranking algorithms rank the features by a metric and eliminate all features that do not achieve an adequate score. Good examples of this can be found in [5, 6]. Subset selection algorithms search the set of possible features for the optimal subset and automatically eliminate the irrelevant ones. Examples include the algorithms used in software programs such as SPSS, Minitab, Statistica and those algorithms used in machine learning such as the Least Square Fitting algorithm [7, 8, 9]. With the recent advances in data acquisition tools in the petroleum industry such as Logging While Drilling (LWD) and Measurement While Drilling (MWD), many logs are produced and there is the need to extract from these logs only those that are most relevant to our target reservoir properties [10, 11].

Petroleum reservoir characterization is the process of quantitatively describing various reservoir properties in spatial variability by using available field

data. This process plays a crucial role in modern reservoir management: making sound reservoir decisions and improving the reliability of the reservoir predictions. The ultimate goal is a reservoir model with acceptance tolerance for imprecision and uncertainty [12, 13]. The two fundamental reservoir properties that relate to the amount of fluid contained in a petroleum reservoir and its ability to flow and that make significant impacts on petroleum field operations and reservoir management are porosity and permeability [12].

Computational Intelligence (CI) schemes have been used in petroleum reservoir modeling. These include: Radial Basis Function, Bayesian Belief Networks, Naïve Bayes, Random Forests, FN, SVM, T2FL, Artificial Neural Networks, Adaptive-Neuro Fuzzy Systems, Extreme Learning Machines and Decision Trees. However, the dominant input parameters are usually selected using statistical tools. Our position is that such non-linear phenomena as temperature, pressure, volume, drive mechanism, structure and seal, well spacing, well-bore integrity, porosity and permeability could not be adequately handled with linear tools and algorithms [13, 14]. In addition to the non-linearity, these algorithms are also offline in the sense that they are not seamlessly connected to the CI techniques. The former are used separately from the latter. Hence, the output of the algorithms has to be manually transported to the CI techniques for further processing. There are many problems associated with this such as delayed processing, the need for many tools at the same time and the inefficiency involved in doing all these. Hence, there is the need for need for hybrid solutions that will incorporate both the feature selection process with a chosen CI technique for effective and seamless petroleum reservoir modeling.

To achieve the objective of this study, we propose an FN-based T2FL-SVM hybrid model. Our major motivation for this study is the quest for higher performance accuracy in the prediction of petroleum reservoir properties through the use of the most relevant logs and thus, removing those logs that may only end up polluting our predictive models.

LITERATURE SURVEY

This section reviews the literature about the feature selection process, hybrid CI, a brief overview and the areas of successful application of each of the components of the proposed hybrid model within and outside the petroleum industry.

Feature Selection

In statistics, the most popular form of feature selection is stepwise regression [15]. It is a greedy algorithm that adds the best feature (or deletes the worst feature) at each round of the selection process. The main control issue is deciding when to stop the algorithm. In machine learning, this is typically done by cross-validation. More robust methods have been explored, such as branch and bound and piecewise linear network. Feature selection is a process used to evaluate a subset of features as a group for suitability. Subset selection algorithms can be broken into Wrappers, Filters and Embedded types. Wrappers use a search algorithm to search through the space of possible features and evaluate each subset by running a model on the subset. Wrappers can be computationally expensive and have a risk of over fitting to the model. Filters are similar to Wrappers in the search approach, but instead of evaluating against a model, a simpler filter is evaluated. Embedded techniques are embedded in and specific to a model [15].

Many popular search approaches use greedy hill climbing, which iteratively evaluates a candidate subset of features, then modifies the subset and decides if the new subset is an improvement over the previous. Evaluation of the subsets requires a scoring metric that grades a subset of features. Exhaustive search is generally impractical, so at some defined stopping point, the subset of features with the highest score discovered up to that point is selected as the satisfactory feature subset. The stopping criterion varies by algorithm; possible criteria include: a subset score exceeds a threshold, a program's maximum allowed run time has been surpassed, etc. [2, 3, 11].

Ref. [16] proposed a genetic polynomial regression technique to select the significant input variables for the prediction of the engine load in a combine harvester. The results of the Genetic Algorithm (GA)-Based algorithm were compared with those of the ordinary Cross-Correlation Analysis and they were found to be more consistent. However, GA with its exhaustive search algorithm has been known for its long execution time and its need for high processing power due to its complexity. Similarly, [17] provided a procedure of feature selection to train neural networks using binary particle swarm optimization (PSO). The results agreed with theoretical expectation and could be developed further for finding sensitivity value which tells the importance of each input as well. However, similar to GA, PSO is time-consuming and memory-intensive due to its complexity.

Other studies used Mutual Information [18] while [19] presented a review of other methods used in

feature selection such as depth-first search, breadth-first search, heuristic search, random search, forward selection, backward elimination, model-free methods and measure of probability of errors.

To the best of our knowledge, FN has not been discovered as a feature selection technique despite its excellent functional approximation and model selection capabilities.

Hybrid Computational Intelligence

An approach resulting from the combination of two or more techniques is called a hybrid. It has also been defined as an approach that combines different theoretical backgrounds and algorithms such as data mining and soft computing methodologies. The main idea behind hybridization is to complement the weaknesses of one technique with the strength of other techniques. Since no single technique is good for everything and in all situations, there is a need to combine the individual capabilities of each technique to obtain a more versatile and robust technique [11].

A number of hybrid techniques have been reported in literature with very few studies in the petroleum industry, which is the focus area of our application. The few studies reported in the petroleum industry include [20] which combined GA with Neural Networks for the permeability estimation of a reservoir. Ref. [21] combined Neural Network with Hidden Markov Models for Lithology identification in the Triassic Province in Algeria. For the same province, [22] also combined Neural Network with Radial-Bias Functions for reservoir characterization. [23] combined Genetic Programming with Fuzzy/Neural Inference Approach to estimate permeability.

All these hybrid techniques neither used FN algorithm in any form nor implemented any straight-forward feature selection procedure. Hence, our proposed hybrid model stands out uniquely in the body of existing knowledge.

Components of the Hybrid Models

The proposed model comprises SVM, T2FLS and the FN's model selection algorithm. These will be explained briefly with more details on the FN component since it constitutes the basis for the admirable performance of the proposed hybrid model.

Support Vector Machines

SVM is a set of related supervised learning methods used for classification and regression. It belongs to a family of generalized Linear Classifiers. It

can also be considered as a special case of Tikhonov Regularization. SVM maps input vectors to a higher dimensional space, which is called a feature space, where a maximal separating hyper plane is constructed. More references to the structure of SVM and its applications can be found in [11 - 14].

Type-2 Fuzzy Logic System

T2FLS was introduced as an extension of the concept of Type1 Fuzzy Logic System. T2FLS has membership grades that are themselves fuzzy. For each value of a primary variable (e.g., pressure and temperature), the membership is a function (not just a point value). The secondary Membership Function (MF) has its domain in the interval (0, 1), and its range may also be in (0, 1). Hence, the MF of a T2FLS is three-dimensional, and it is the newly introduced third dimension that provides new degrees of design freedom for handling uncertainties. T2FLS does not obtain good performance when the number of training data is small, but it can perform better when the number of training prototypes is large. Further descriptions of the concepts of FLS, including Type-2 and its applications can be found in [11 - 14].

Functional Networks

FN is an extension of Artificial Neural Networks (ANN). It consists of different layers of neurons connected by links. Each computing unit or neuron performs a simple calculation: a scalar typically monotone function f of a weighted sum of inputs. The function f , associated with the neurons, is fixed and the weights are learned from data using some well-known algorithms such as the least-square fitting.

A FN consists of a layer of containing the input data; a layer of output units containing the output data; one or several layers of neurons or computing units which evaluate a set of input values, coming from the input units, and which give a set of output values to the output units. The computing units are connected to each other, in the sense that the output from one unit can serve as part of the input to another neuron. Once the input values are given, the output is determined by the neuron type, which can be defined by a function [11 - 14]. FN is different from the traditional ANN in that the weights which must be learned in the latter do not appear in the former. Instead, neural functions are learned. In ANN, the outputs of the neurons are different, while in FN, they can be coincidental. This leads to a set of functional equations which have to be solved. Lastly, in ANN, the neural functions are univariate while in FNs, they can be multivariate.

EXPERIMENTAL DESIGN

This section explains the details of the study starting from a succinct description of the datasets used, the criteria used to evaluate the performance of the proposed model and the experiment design of the study.

Description of Data

A total of six datasets for porosity and permeability obtained from two petroleum reservoirs were used for the design, testing and validation of this study. The three well logs for porosity were obtained from a drilling site in the Northern Marion Platform in North America (Site 1) and the three for permeability from a drilling site in the Middle East (Site 2). The datasets from Site 1 has six predictor variables for porosity while the dataset from Site 2 has eight predictor variables for permeability. Each of the datasets was divided into training and testing sets by using a stratified sampling technique which randomly divides the data into training and testing sets in the 70:30 ratio. This division strategy reserves 70% of the data was used for training and testing while the remaining 30% was used for validation.

Experimental Design

Correlation Coefficient (CC) and Execution Time (ET) were used as the criteria for evaluating the results of this study while basing the methodology of our study on the standard CI approach to the hybridization paradigm using FL, SVM and FN. These techniques were used to develop a hybrid model consisting of Functional Networks, Type-2 Fuzzy Logic and SVM (FN-T2F-SVM). We used the Least Square SVM, the Interval Type-2 Fuzzy Logic System and the Iterative Least-Squares Functional Networks (LSFN), all in MATLAB platform. In order to benchmark the efficiency of the FN algorithm, we also implemented a T2F-SVM hybrid model but without the FN component.

The hybrid models were designed and optimally tuned to benefit immensely from the strengths of the individual techniques, to complement the weaknesses of one technique with the advantages of the others, and hence to combine the cooperative and competitive characteristics of the individual techniques. On the reasons for the choosing Type-2 FL and SVM, readers are referred to [13, 14]. Since the role of FN in the hybrid models is the main focus of this paper, this will be discussed in more details.

Functional Networks Design Methodology

The Least Squares Fitting algorithm was used for the implementation of the Associative FN. This algorithm has the ability to learn itself and to use the input data directly, by minimizing the sum of squared errors to obtain the parameters namely the number of neurons and the type of kernel functions needed for the training process. It works by building an initial model, simplifying the model and selecting the best parameters for the simplified model. The overall process comprises the model initialization and selection modules.

In the model initialization module, the values of porosity and permeability of a well were determined by the dataset input parameters. The parameters (represented here by x , y , z for simplicity and demonstration purpose) were modeled in an initial network like the one shown in Figure 1 and reduced to the simplified version equivalent of the initial network as shown in Figure 2.

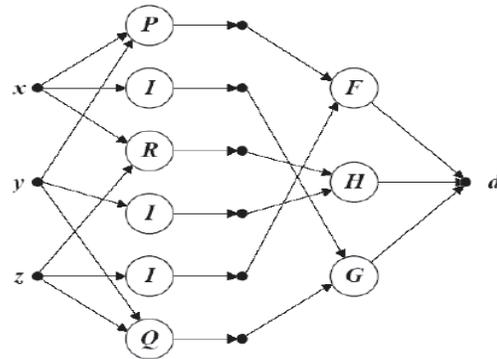


FIGURE 1. Initial Topology of the Functional Network Corresponding to the Combined Functional Equations.

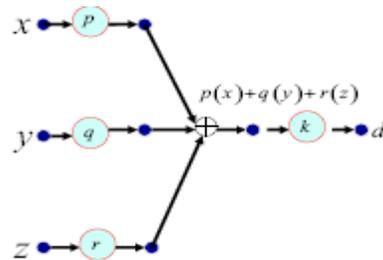


FIGURE 2. The Simplified Network.

In the model selection module, the best model was selected using the Minimum Description Length (MDL) principle [24]. This measure allows comparisons not only of the quality of different approximations, but also of different FN models. It was also used to compare models with different parameters, because it has a penalty term for overfitting. Moreover, it is distribution-independent. This makes it a convenient method for solving the model selection problem. Accordingly, the best FN model for a given problem corresponds to the one with the smallest description length value. This was calculated using the backward-elimination and forward-selection methods.

The backward elimination process starts with the complete model with all parameters and sequentially removes the one that will not lead the model to the smallest value of the MDL measure. The process is repeated until there is no further improvement in the measure. Next, the forward selection process started by taking the final model of the backward process and sequentially added the variable that would lead to the smallest value of MDL measure. This process was repeated until no further improvement in the MDL measure was obtained either by removing or adding a single variable.

In summary, the learning process of the LS-based FN algorithm consists of obtaining the neural functions from a set of training data by minimizing the sum of squared errors between the input and the target output and suggesting an approximation to each of the functions while selecting the best among them.

The results are presented and discussed in the next section.

RESULTS AND DISCUSSIONS

The significant role of FN in this work was remarkably demonstrated by the reduction in the dimensionality of the datasets for porosity from six to four namely: Parameters 2, 3, 4 and 5, according to their relevance in the system (Table 1). Similarly, the dimensionality of the datasets for permeability was reduced from eight to four namely: Parameters 2, 3, 4 and 6.

TABLE 1. Initial and Selected Parameters for Porosity.

| | |
|--------------------------|--|
| Initial Variables | 6: Core, Top Interval, Grain Density, Grain Volume, Length and Diameter |
| Selected by FN | 4: Top Interval, Grain Density, Grain Volume and Length. |

TABLE 2. Initial and Selected Parameters for Permeability.

| | |
|--------------------------|--|
| Initial Variables | 8: GR, PHIE, RHOB, SWT, RT, MSFL, NPHI and CALI |
| Selected by FN | 4: PHIE, RHOB, SWT and MSFL |

The experiment was performed with the two hybrid models simultaneously. The same datasets were passed through the FN-T2F-SVM and T2F-SVM. The results of the experiment are shown in Table 3 and 4 and plotted in Figure 3 through 8.

TABLE 3. Results of Porosity Correlation Coefficient and Execution Time.

| Hybrid Models | CC | | Execution Time | |
|-------------------|----------|---------|----------------|---------|
| | Training | Testing | Training | Testing |
| Well 1 | | | | |
| FN-T2F-SVM | 0.943 | 0.969 | 60.979 | 8.214 |
| T2F-SVM | 0.823 | 0.792 | 265.865 | 57.312 |
| Well 2 | | | | |
| FN-T2F-SVM | 0.832 | 0.818 | 27.343 | 4.411 |
| T2F-SVM | 0.791 | 0.785 | 143.381 | 23.624 |
| Well 3 | | | | |
| FN-T2F-SVM | 0.936 | 0.936 | 0.494 | 0.042 |
| T2F-SVM | 0.852 | 0.838 | 1.385 | 0.157 |

TABLE 4. Results of Permeability Correlation Coefficient and Execution Time.

| Hybrids | CC | | Execution Time | |
|-------------------|----------|---------|----------------|---------|
| | Training | Testing | Training | Testing |
| Well 1 | | | | |
| FN-T2F-SVM | 0.903 | 0.879 | 43.333 | 6.231 |
| T2F-SVM | 0.835 | 0.813 | 361.253 | 71.441 |
| Well 2 | | | | |
| FN-T2F-SVM | 0.891 | 0.885 | 81.512 | 11.211 |
| T2F-SVM | 0.857 | 0.832 | 636.232 | 129.642 |
| Well 3 | | | | |
| FN-T2F-SVM | 0.798 | 0.810 | 51.885 | 7.792 |
| T2F-SVM | 0.761 | 0.732 | 556.225 | 109.112 |

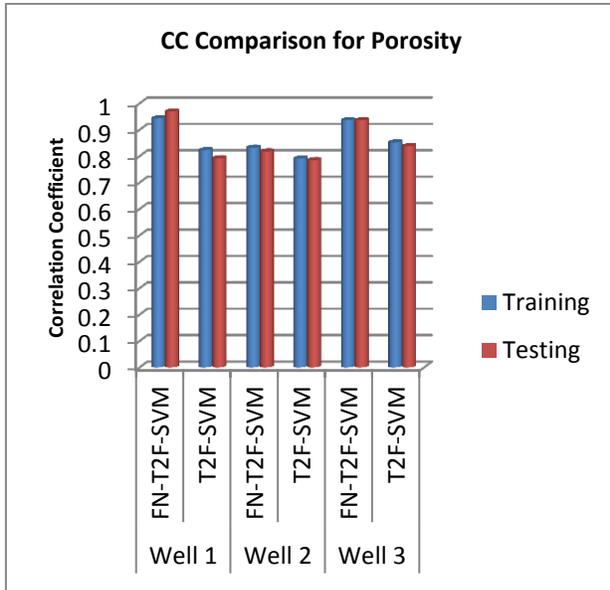


FIGURE 3. Comparison of Correlation Coefficient for Porosity on Wells 1, 2 and 3.

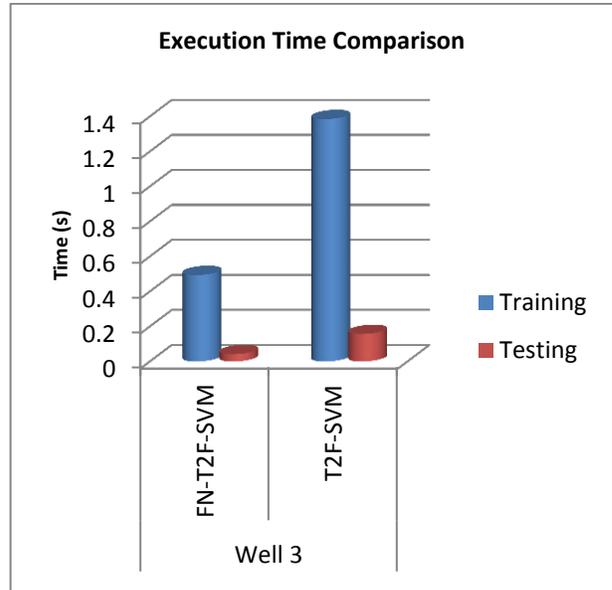


FIGURE 5. Comparison of Execution Time for Porosity on Well 3.

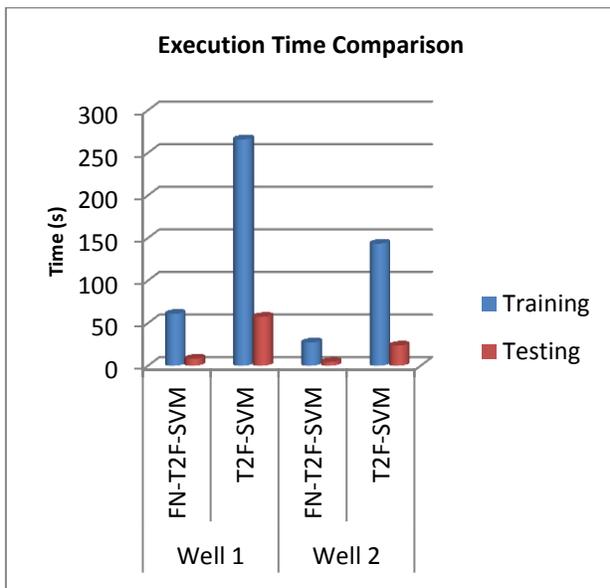


FIGURE 4. Comparison of Execution Time for Porosity on Wells 1 and 2.

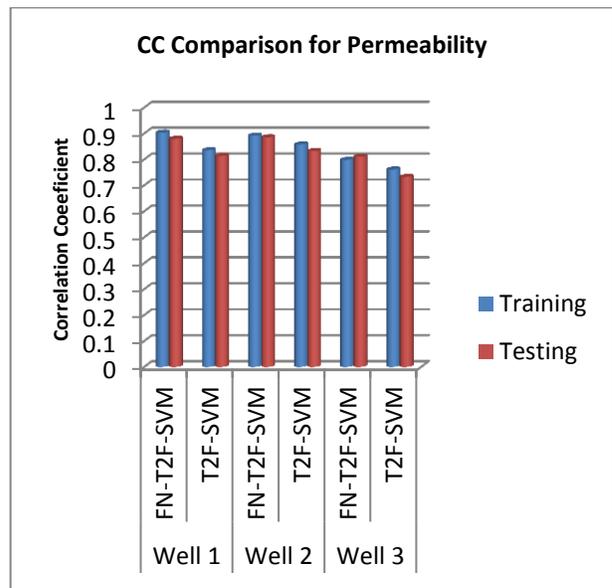


FIGURE 6. Comparison Correlation Coefficient for Permeability on all Wells 1, 2 and 3.

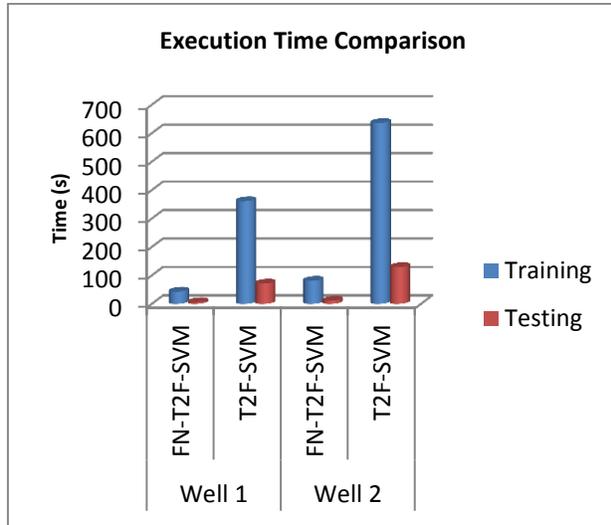


FIGURE 7. Comparison Execution Time for Permeability on Wells 1 and 2.

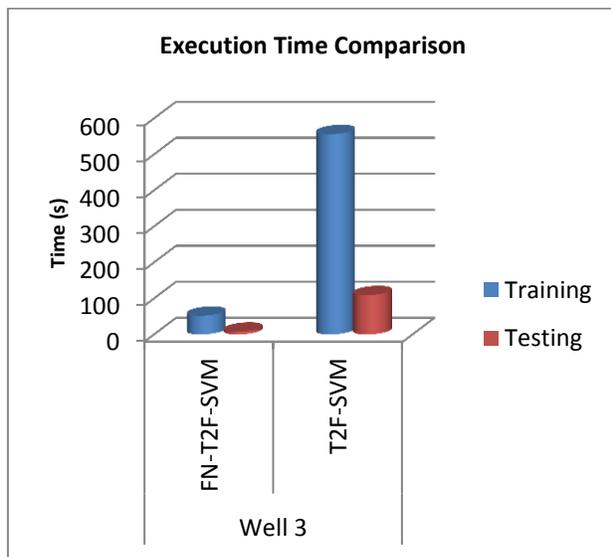


FIGURE 8. Comparison Execution Time for Permeability on Well 3.

As shown in Table 1 and 2, the FN component of the FN-T2F-SVM hybrid model extracted only four parameters that were found to be dominant out of the six parameters for porosity and eight for permeability. Using these selected parameters increased the overall performance of the hybrid models.

In terms of CC for porosity, Figure 3 shows that the training and testing performance of the FN-T2F-SVM hybrid where FN was used as a best model

selector was better than that of the T2F-SVM hybrid without the FN component. This clearly shows the effect of using only the relevant variables and this procedure could be attributed to the excellent performance of the FN component. In terms of ET, Figure 4 and 5 showed that the FN-T2F-SVM hybrid executed faster than the T2F-SVM hybrid model. This is due to the reduced dimensionality that accompanied the best model selected by the FN component in the FN-T2F-SVM hybrid model. Usually, a best-subset selection procedure is accompanied by a reduction in the dimensionality of the selected dataset since some of the parameters found less relevant would have been removed.

The same trend was observed in the case of permeability prediction. As shown in Figure 6, the training and testing correlations for the FN-T2F-SVM hybrid were higher than those of the T2F-SVM hybrid model. This indicated the former performed better than the latter. Also, the execution times of the FN-T2F-SVM hybrid model were less than those of the T2F-SVM hybrid as shown in Figure 7 and 8. The same reason applies here as for the porosity prediction.

Interestingly, the FN-T2F-SVM model despite comprising three components still performed better than the T2F-SVM with only two components. This indicates that performance is not about numbers but rather efficiency. Despite that the former has more number of components; it was favored by the feature selection process which improved its performance. Hence, the proposed FN algorithm has proven to be a good feature selection algorithm that can be recommended to the petroleum industry.

CONCLUSION

This study presented the efficient role of the FN learning algorithm as a best-model selector by carrying out a comparative study on the performance of two hybrid models, one with FN and the other without it. The FN-T2F-SVM hybrid model used the least square based FN learning algorithm to extract the best parameters from the porosity and permeability datasets resulting in a reduced dimensionality. This resulted in the reduced search space of the other components of the hybrid model and also improved the overall performance since only the most relevant parameters were extracted and used. This has been demonstrated by the higher correlation coefficients and the lower execution times of the FN-T2F-SVM hybrid over the T2F-SVM hybrid.

A future study will focus on the effect of the best-model selection capability of FN on other techniques

such as Extreme Learning Machine and Artificial Neural Networks.

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